

# ESTEP 2025 Annual Event

28-30 October 2025  
Udine (ITALY)

How decarbonisation, digitisation  
and circular solutions forge the  
sustainable European steel future?

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# ALCHIMIA: Federated and Continual Learning for Sustainable and Competitive Steelmaking



DIGIMET



DANIEMI AUTOMATION



UNIVERSITÀ  
DEGLI STUDI  
DI UDINE  
HIC SUNT FUTURA

# PROJECT CONTEXT

## 1- Scrap processing

- **3 CELSA plants:** BCN, POL and FR
- 2 modelling approaches:
  - **Analytical models:** physic-based model  
Dynamic mass & energy balances (BFI)
  - **Neural models (FFNNs)**  
Temperature & Chem prediction (SSSA)
- **Goal**  
Enable cross-plant learning without data sharing



**SMARTER, GREENER  
PROCESSES VIA  
DISTRIBUTED AI**



# WHY FEDERATED AND CONTINUAL LEARNING?

- **Federated Learning (FL)**

Local training + Global aggregation

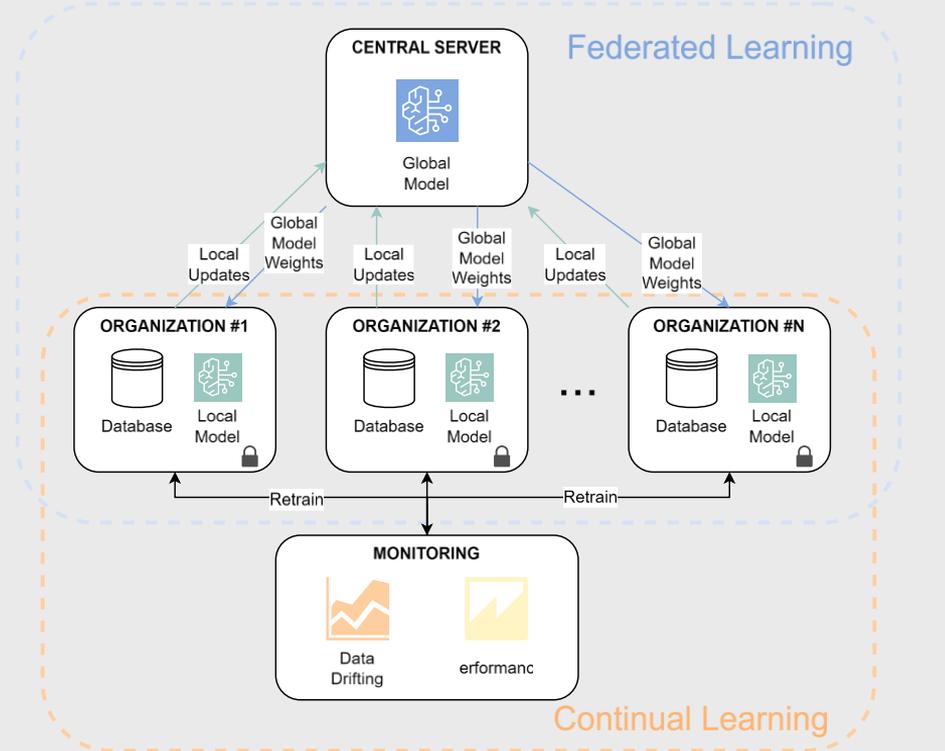
- **Continual Learning (CL)**

Monitors model drift + Automatic retrain

- **Together FL + CL**

- Enable **cross-plant collaboration** while preserving privacy and data ownership
- **Maintain model performance** in evolving industrial conditions
- Build adaptive and trustworthy systems for **long-term solutions**

**EVIDEN**  
an atos business



# CELSA USE CASE

- 2 Processes x 3 Plants = **6 models developed**

- EAF Dynamic Process Model
- Ladle Furnace Neural Model

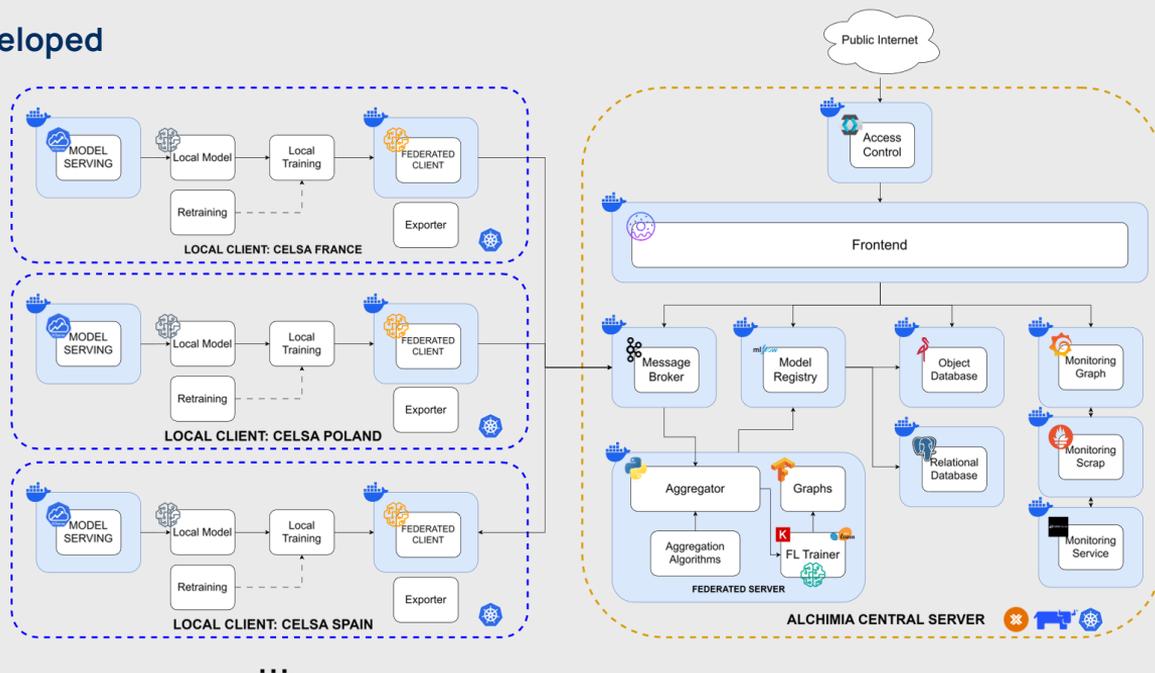
- **Unified data schema & ETL pipeline**

- **Federated Learning (FL)**

- Local training on each plant's data
- Model weights → securely sent → ATOS central server
- Global aggregation (FedAvg) → updated model redistributed

- **Continual Learning (CL)**

- Real-time monitoring of model performance
- Automatic drift detection (e.g., scrap mix, sensor drift)
- Trigger local retraining → updated weights → federated update
- Extends model lifespan & stability; reduces maintenance cost



# FEDERATED LEARNING ON ANALYTICAL EAF MODELS

- **Model type:** Analytical mass–energy balance model for Electric Arc Furnace (EAF) developed by BFI
- **Objective:** Evaluate whether EAF model can be jointly optimized via FL without sharing plant data
- **Clients:** CELSA Plant 1 (187 heats), CELSA Plant 2 (60 heats), CELSA Plant 3 (108 heats)
- **Shared elements:** Local model parameters (efficiency factors, energy terms)
- **Method:**
  - Iterative **least-squares optimization** per plant → **Parameter aggregation** on ATOS server
  - Tested different **MAX\_NFEV** settings and **weighting strategies** (simple, weighted, inverse weighted)
- **Findings:**
  - **Limited improvement over local models** (heterogeneous data)
  - While 2 plants benefited; the third diverged (sensor differences, noise)
  - **Inverse weighting** during aggregation gave best results
- **Key takeaway:**

FL requires harmonized datasets and consistent operating regimes

# FEDERATED LEARNING ON ANALYTICAL EAF MODELS

- Baseline MAE values for the local models:

- MAE PLANT 1 = 16,50
- MAE PLANT 2 = 15,95
- MAE PLANT 3 = 21,62

- **MAX\_NFEV** Maximum Number of Function Evaluations

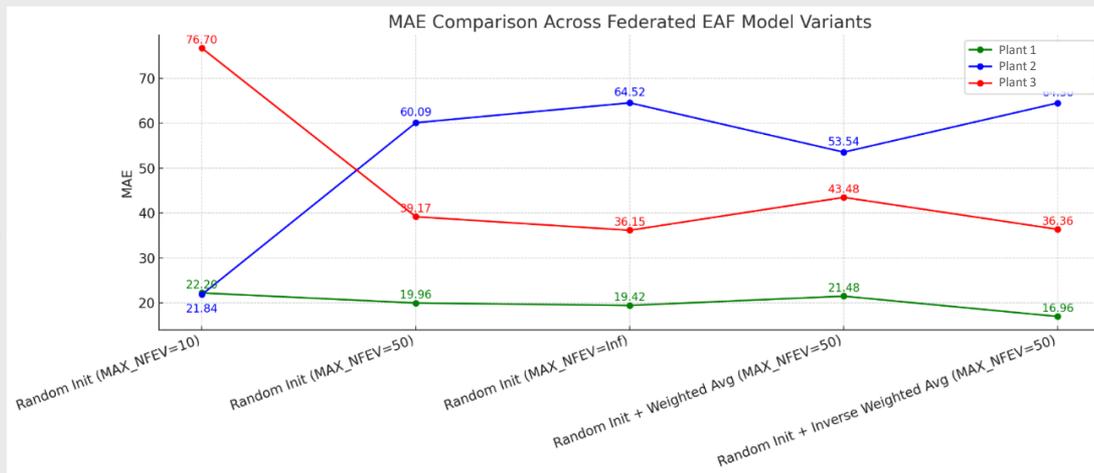
- PLANT 2 is the smaller plant with most noisy dataset which requires more steps to converge

- **Findings:**

- **Limited improvement** over local models (heterogeneous data)
- Plants 1 and 3 show a shared improvement trend, suggesting that they operate within **compatible ranges**
- Plant 2 tends to perform worse when the other clients improve (sensor differences, distinct operating curves)
- **Inverse weighting** during aggregation gave best results

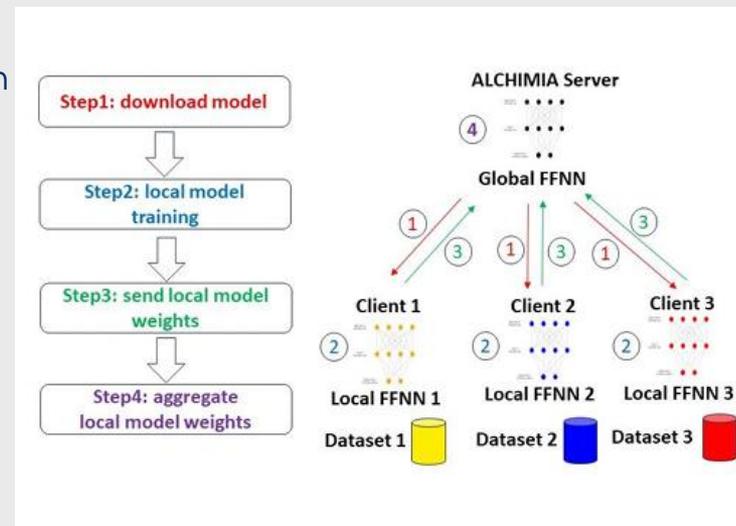
- **Key takeaway:**

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# EXPERIMENTS ON NEURAL MODELS (LF)

- **Model type:** Feed-Forward Neural Network (FFNN)
- **Objective:** Predict final steel temperature & chemical composition
- **Clients:** CELSA France, CELSA Spain (BCN), CELSA Poland (PL)
- **Shared elements:** Model weights (privacy-preserved) – no raw data exchange
- **Method:**
  - Local training → send weights → Central **aggregation** → Update global model → **Redistribute**
  - Continual Learning monitors drift & **retrains** automatically
- **Findings:**
  - Global model **outperforms** all local models (MSE ↓ ≈15%)
  - **Strong generalisation** across plants and operating conditions
  - **Stable performance** maintained via Continual Learning
- **Key takeaway**  
Federated neural models are more adaptable to plant variability than analytical ones



# INDUSTRIAL INTEGRATION & ACKNOWLEDGEMENTS

- Full integration under development - **Validation phase Q4 2025**
- Towards “**AI-ready plants**”: secure, self-learning systems
- **Framework reusability** for other process industries
- **Technology developed** by EVIDEN (ATOS) team:
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  - Raquel Lazcano - [raquel.lazcano@eviden.com](mailto:raquel.lazcano@eviden.com)
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- **Industrial validation** by CELSA Group
  - David Blazquez – [david.Blazquez@gcelsa.com](mailto:david.Blazquez@gcelsa.com)
- Horizon Europe project **ALCHIMIA** – Data and decentralized AI for Green Metallurgy.



**CELSA**

Thank you!